

On the Sensitivity of Geo-based Content Sharing to Location Errors

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Abstract—A number of opportunistic content sharing services were developed that exploit device-to-device contacts for infrastructure-less operation, including Floating Content, Locus, and Hovering Information. All of them depend, like geo-based ad-hoc routing protocols, on mobile devices knowing their respective geo locations to accurately perform data replication. In this paper, we explore the impact of different types of location errors on the performance of such a service. We use a GPS error distribution for mobiles derived from real-world measurements, consider different frequencies for GPS readings, and account for only subsets of mobile devices actively using GPS. We carry out extensive simulation studies using synthetic mobility models as well as real-world traces to assess the impact of different types of errors. We find that, overall, opportunistic content sharing is quite robust provided that a sufficient number of nodes support GPS and allow the others to have a rough estimate of where they are. Whether or not the GPS position is prone to errors affects some scenarios and is almost negligible in others.

I. INTRODUCTION

A number of geo-based content sharing systems have been proposed in the past, including Floating Content [1], Hovering Information [2], Locus [3], and Ad Loc [4], among others. While details differ, by and large these systems share the conceptual idea of *anchoring* a piece of content in a physical location and making it available to other nodes within a maximum distance from this location; can jointly refer to these parameters comprising the origin and the replication (and availability radius) as the *anchor zone* [5]. A key property of all the above systems is that they do not rely on infrastructure nodes or cloud services to ensure data availability but rather replicate content items within the anchor zone among mobile nodes in a device-to-device (peer-to-peer) fashion. While this operation does not require infrastructure network access—and thus limits dependencies as well as vulnerability to third party actions such as traceability or censorship—it comes at the cost of unpredictability: there is no guarantee that content “posted” to an anchor zone will remain available. We refer to this property as best-effort (probabilistic) content sharing.

Obviously, the operation of such a system depends on the number of nodes that move through the anchor zone and are thus available for replication (for which we can state lower [6] and practical bounds [7]). But, in addition, it is crucial that the nodes in the system know where they are in order to be able to execute location-based content replication in a fully distributed system in the first place.

In principle, obtaining location information is largely trivial

on today’s smart mobile devices by using the Global Positioning System (GPS) or Assisted GPS. In practice, however, running GPS all the time consumes substantial amounts of energy and thus noticeably reduce battery lifetime. As a result, not all mobile nodes may have GPS enabled all the time, or they may active GPS only in certain intervals. Moreover, depending on the environment, reported GPS positions may be prone to position errors.

In this paper, we explore the impact of position errors on the performance of geo-based information sharing using *Floating Content* as a reference service. We review related work in section II, briefly summarize the operation of Floating Content in section III, and then introduce our error model and error modes in section IV. We present the evaluation setup in section V and present our results in section VI before we conclude in section VII with a brief assessment and hint at future work.

II. RELATED WORK

Previous geo-based routing protocols such as GeoCast [8], LAR [9], DREAM [10], and GPSR [11] were proposed based on the assumption that each node knows its location coordinates from GPS. However, in mobile environment GPS signal could be obstructed in many places including tunnels, underground, or anywhere else where the satellite signal is blocked [12]. In addition, due to the limited energy and computing power in MANET, it is not practical to keep active the GPS signal of every node all the time. Some of the relevant GPS error modeling techniques and location-based routing protocols in the ad-hoc network are discussed in this section.

Several geo-routing protocols have been proposed to address GPS related errors and to estimate the position of the node of interest in a mobile ad hoc networks (MANET). There are surveys [12], [13] that summarize, compare and contrast some early efforts on position-based routing in MANET. Grid-based on-road localization (GOT) [14], developed to improve location accuracy calculation by allowing the vehicle to vehicle message (beacons) exchange in self-organized VANET, where some of the vehicles in the network have inaccurate or blocked GPS signal. One downside of this system is that its accuracy highly depends on the number of vehicles with GPS signal and signal accepting threshold. Similarly, [15] presented location estimation method for GPS-unequipped vehicles using a minimum of three GPS-equipped vehicles as a reference point. GPS-unequipped vehicles required to communicate with a minimum of three GPS-equipped vehicles, which suffers the

accuracy of location estimation, especially during low traffic density. Another geo-based routing protocols [16] proposes that only a device that serves as a G-node need to be equipped with GPS for determining the location of other (GPS-unequipped) nodes, as long as unequipped nodes manage to know the position of a nearby G-node node.

The negative impact of GPS error in geo-based ad-hoc routing in VANETs is analyzed by [17]. The authors show that positioning errors can degrade the performance of geo-based routing, by increasing the failure probability of route discovery and the hop-count. Similarly, [18] studies the effect of GPS error using distance degradation of each hop to find that the performance of VANET is significantly affected by GPS errors.

A modular positioning system that uses various positioning sources (GNSS, GSM, and Wi-Fi), based on the quality of the measured signal is proposed by [19]. In [19], if GPS signal is not available or has low quality, Wi-Fi or GSM measurements are read by the mobile device and sent to the localization server. The localization server is responsible for estimating the mobile devices position. GPS error modeling [20] focused on localization accuracy by creating a collaboration among mobile nodes that are capable of localizing themselves using GPS or pedestrian dead reckoning. Simulation in [20] uses a simple random mobility model and shows that the magnitude of GPS error ranges up to several tens meters.

In our work, we focus on geo-based content sharing where content items are kept at rather than routed to a location, and we use extensive measurements for our GPS error model.

III. FLOATING CONTENT OPERATION

We base our work and terminology on the Floating Content model [7]. We assume smart mobile devices equipped with short-range radios such as Bluetooth or WLAN plus suitable communication stacks that allow them to detect peers in their proximity, set up connection to, and exchange information with them. Despite limitations of mobile operating systems, solutions such as WLAN-Opp [21] can offer connectivity between peers and opportunistic networking platforms such as Hagggle [22], PodNet [23], SCAMPI [24], or Twimight [25] implement the content replication services on top.

The Floating Content model defines, for each content item I , an anchor zone comprising its origin (or: anchor point) P , a replication range r , and an availability range a (cf. Figure 1a). Within radius r from P , a content item is replicated by a node whenever it encounters another node. Between r and a , a node holding the content item will be passive, i.e., continue carrying the item but not replicating it anymore. When a node is more than a away from P a content item is deleted (when meeting another node).¹

Each item I has a size s_I and an associated lifetime (TTL) T_I ; after its lifetime expires, it will automatically be deleted (“garbage collection”). Together with the availability range a ,

¹We have experimented with many different replication and deletion policies and found that the simplest one described here yields very good results and is practical to implement. [7]

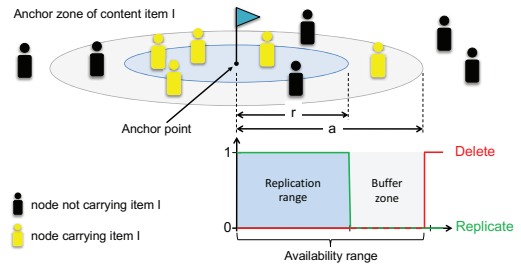


Fig. 1. An anchor zone of an item, mobile nodes and their communication ranges: a node will replicate a content within r from the anchor point, delete an item when further away than a and just hold on to the item in-between.

these two properties define the potential total resource usage in the distributed system: all nodes within a_I from P_I may hold a copy of I for TTL seconds and use up s_I memory during this period. We have used this total resource usage to prioritize content items for replication: those with the least demands would be replicated first. This policy (“STF2” in [7]) computes per content item a priority $p_I = a_I^2 \times s_I \times T_I$ and then sends content items in ascending order of p_I . This policy encourages users to use the minimum necessary resources (anchor zone area and TTL) when posting an item.

In this paper, we extend this policy further to break ties between messages of equal size. The reason is that to focus the evaluation on GPS errors, we consider equal-sized messages with identical TTLs and equal anchor zones, thus all p_I ’s are identical. Let d_I be the distance of a node to the origin P_I when encountering another node. We then define $p_I' = d_I \times p_I$ so that items further away from its origin have a lower replication priority. All our simulations use this refined policy termed “SDTF2”.

IV. POSITION ERRORS

We consider three types of position errors discussed in the following: 1) GPS not active or unavailable; 2) GPS update (or: reading) interval; and 3) GPS position errors.

A. GPS Availability

We define ρ to be the fraction of nodes that have an active GPS device, which may or may not have position errors as per 3). A node without GPS is initialized to have no valid position. As long as it does not have a valid position, the node will not create content items, nor exchange items with other nodes. However, a node may obtain a valid position when it comes in contact with at least one other node that does have a valid position. Let n be the number of peer nodes with a valid position a node A comes in contact with. It then obtains the positions $(x_i, y_i), 1 \leq i \leq n$ from all those nodes and computes its own position as the average of the other node positions: $(x_a, y_a) = (1/n \sum_{i=1}^n x_i, 1/n \sum_{i=1}^n y_i)$.

We define two policies for obtaining a valid position from another node; they define the expectation on the accuracy of the other node’s position information: 1) *GPS-only* only accept a valid position from a peer node if it has its own active GPS and thus delivers first-hand information. This policy yields higher accuracy for the position information inferred from

others but limits “priming” other nodes with valid positions to those with GPS. 2) *Indirect* just requires the other node to have any valid position, including having obtained it from a third party. We do not impose any limit on how old the last update to the valid position is and we do not differentiate between GPS-based and indirect positions when computing the position average. This second policy allows transitive propagation of position information—and thus introduces potentially faster spreading of valid position at the risk of this information being less accurate or outdated.

B. GPS Reading Interval

We define a parameter δ to indicate the interval in seconds in which the GPS device will be (activated and) read. If the device is read at t_0 the retrieved position information is cached. Requests from the Floating Content system will always use the cached value for all operations, i.e., no matter how fast a node moves, the retrieved position information will not change during $[t_0, t_0 + \delta)$.

C. GPS Errors

We finally define a simple GPS error model. The accuracy of GPS position information depends on many factors, including: the GPS device itself and its firmware; the operating environment, especially how well the sky is visible and how many GPS satellites can be seen; and, for assisted GPS, how many additional cues are available. Here we focus on plain GPS.

Because of the above dependencies, we use a trace-based approach to estimate reasonable GPS errors. To this end, we rely on the *NetRadar* [26] measurement platform. NetRadar provides mobile users (on virtually all mobile operating system platforms) with a tool to obtain instant performance measurements of their respective cellular (or WLAN) connectivity. These measurements are usually taken on-demand by the user (even though automated background operation is possible), so that they are irregular in time and space. Along with the results of the performance measurements (such as uplink/downlink bit rate, RTT) the system collects in an anonymized form the GPS location and the GPS location error as reported by the mobile device, plus further metadata such as the device type. The NetRadar platform aggregates the anonymized data and offers a geographic overview of the mobile network performance.

We have mined the NetRadar database for the GPS data for 2014 and 2015. To be in line with our simulation environment (we use Helsinki for synthetic mobility traces, see below) we extracted only those data points from within the Helsinki region. Moreover, we restrict ourselves to 2015 for the most recent data of a complete year so that we likely have more modern mobile devices with better GPS capabilities. Figure 2a) depicts the distribution of GPS errors as per the above measurements, b) shows how the accuracy differs across different device types (which we deliberately do not name). Table I summarizes the statistics per operating system. While there are differences across the device models, those are not so pronounced in absolute terms that we create different error

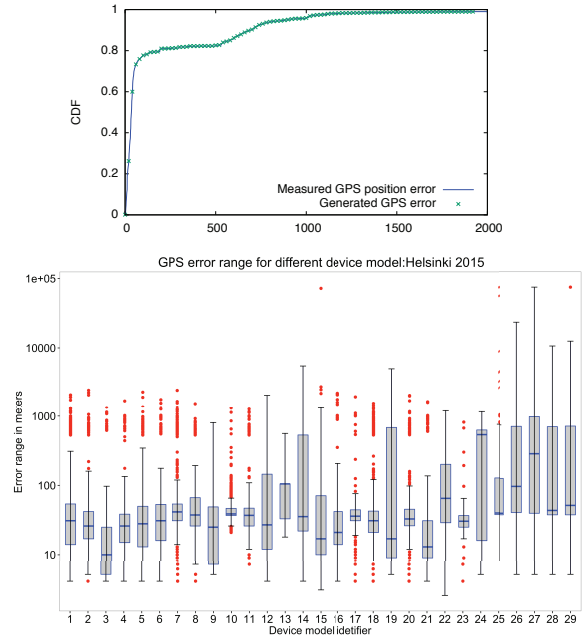


Fig. 2. a) Measured GPS error ranges and errors generated in the simulator (top); b) GPS errors observed across different devices (bottom).

models and use them in our evaluation. We rather create a normalized model across all measurements.

OS platform	Median	Mean	# measurements
Android	34.5 m	160.1 m	922,418
iOS	71.0 m	1265.0 m	68,008
Windows phone	15.0 m	206.6 m	173,929
Qt	99.0 m	174.5 m	39,263
Total	36 m	314.4 m	1,203,619

TABLE I
STATISTICS OF NETRADAR GPS MEASUREMENTS FOR HELSINKI IN 2015
INDICATING THE MEDIAN AND MEAN GPS POSITION ERROR RANGE

To this end, we cap the distribution at 1925m below which fall 99% of the measurements (the maximum value recorded was 74.5km!). We quantify the distribution into steps of 0.1% and create a table within the simulator using those values. We validate the process by generating a error values from this table, shown to match the measured values well in figure 2a) as the dots.

We finally need to transform the GPS error ranges into a model useful for our simulations. Since the measurements taken by NetRadar are mostly point measurements, we cannot observe how stable the position reported by the GPS device is and how the error range changes over time. Therefore, we define a two-stage error process. In the first stage, every ΔU_1 seconds, a node determines its present GPS error range according to the above distribution. Let r_e be the error range determined in this way. The node then picks, uniformly distributed within $[0, r_e]$ a distance and, uniformly distributed within $[0, 2\pi]$, an angle α . These are used to compute a *base error offset* $(\Delta x, \Delta y)$ to the node’s actual position (x_0, y_0) and

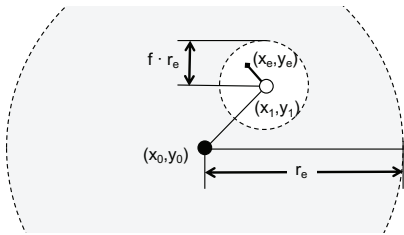


Fig. 3. GPS error generation model with two offsets being computed at different time scales.

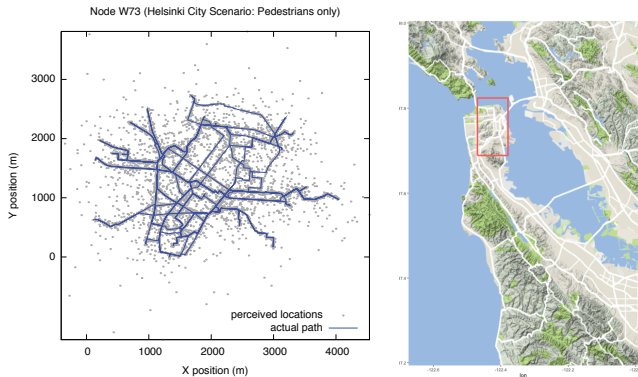


Fig. 4. a) Sample position errors of an individual node (left); b) Area of the San Francisco taxi cab traces (right)

obtain a base error position (x_1, y_1) by adding the base error offset to the actual position. Refer to figure 3. This base error offset remains stable for ΔU_1 to prevent heavy oscillation.

In the second stage, we provide for a smaller-scale oscillation around the base error position. We define a stability interval ΔU_2 at which a second level offset $(\delta x, \delta y)$ is updated. We use the same mechanism as above, choosing a distance and an angle using a uniform distribution to compute the second level offset, but we use only a fraction of r_e for the distance: $[0, f \times r_e]$. Using these, we finally define a node’s GPS position with error as: $(x_e, y_e) = (x_0, y_0) + (\Delta x, \Delta y) + (\delta x, \delta y)$. This means that within ΔU_2 , the error position accurately tracks the node movement, but “jumps” whenever ΔU_1 or ΔU_2 are updated. To illustrate the operation, figure 4a depicts the actual movement of a single node in the Helsinki City Scenario with only pedestrians (HOP), see next section, along with the perceived positions due to GPS errors.

V. SIMULATION ENVIRONMENT

For our simulation-based evaluation, we use the ONE simulator [27], version 1.5.1RC2² that includes the code for Floating Content. We revise and extend the rudimentary code for generating position errors to implement the model described in the previous section, to be included in a github branch. We also implement a new report class to create regular snapshots of ongoing simulations, `SnapshotReport`, and provide a specific subclass to compute absolute position errors

²<https://www.netlab.tkk.fi/tutkimus/dtn/theone/>

of nodes. We use two classes of mobility patterns as described in the following.

A. Synthetic mobility

We choose two different synthetic mobility models: 1) We pick *Random Waypoint (RWP)* in spite of its known deficiencies because its resulting movement, especially with lower node densities, exhibit fewer and shorter contacts than map-based mobility models and thus provide a simple way to explore one extreme in poor connectivity. 2) We also choose the more sophisticated *Helsinki City Scenario (HCS)* [27] based upon a city map (4500×3400) of downtown Helsinki, which we modify to feature only one class of mobile nodes: pedestrians (HOP). They roam the city area like restless tourists following streets and walkways when moving to randomly chosen points on the map following a shortest path using pedestrian speeds of 0.5 – 1.5 m/s. For both scenarios, we use 100, 200, 500, and 1000 nodes.

B. Trace-based mobility

We use the *San Francisco cab traces (SFO)*³ as those offer GPS coordinates (unlike pure contact-based traces) and thus allow evaluating geo-based protocols. These traces were collected from taxi cabs serving in the San Francisco-Oakland area from May 17 to June 10, 2008 (=25 days, with the first and last day of experiment having only half a day of traces). The traces contain records of some 500 vehicles. Each taxi was equipped with a GPS receiver, which was programmed to send location-updates (timestamp, identifier, geo-coordinates) to a central server. The location-updates are quite fine-grained, with the average time interval between two consecutive location updates around 1 minute. Figure 4b depicts the area and the locations of taxi cabs during the first day of the measurements.

Since the original dataset contained a lot of irregularities, it was necessary to prepare the traces and remove inaccurate locations. First, all the data points that correspond to locations in the water were removed. Next, we pruned “jumping” location points, identified as the location updates which would require taxis moving at unusually high speeds between two consecutive points (we used speed value of 50 m/s). Two taxis (numbers 493 and 517) are removed from the trace completely; these taxis kept reporting alternately accurate (or approximately accurate) locations and a few stationary locations, a behavior that did not allow filtering or smoothing the trajectories.⁴ Finally, if two consecutive timestamps of one taxi were more than 30 minutes apart, the interval between those timestamps was considered to be an inactivity period.

These mobility traces are then formatted in accordance with the syntax of the path movement format and fed to the simulator through the `ExternalPathMovementReader`. The path reader uses two files: one for the paths and one for specifying

³<http://crawdad.org/epfl/mobility>

⁴There are still some minor issues that this processing left unchanged, e.g., apparently less accurate location records when vehicles were passing through mountain areas. Further improvements could be made by using options such as “snap to roads” from Google Maps API.

activity times. Nodes follow the paths in the trace file, and pause between paths. Activity times refer to the periods of time when there is valid trace data about the node. While a node is not active, it pauses and will not generate any messages, but it will participate in content replication.

The path reader expects Cartesian coordinates with distance values in meters. Hence, the GPS coordinates have to be transformed into this format. We set the origin of the new coordinate system at point SFcenter (long=-122.446747, lat=37.733795) and translate the trace GPS coordinates into distances from this point. This procedure causes some coordinates to become negative, but the ONE simulator translates and scales the coordinates according to the positive World dimensions. As the traces do provide GPS positions but no error range readings we use the above error model also here.

For the simulations, we choose the following days from the traces with the corresponding number of mobile nodes (taxi cabs):

seed	1	2	3	4	5	6	7	8	9	10
day#	2	4	5	8	9	10	15	17	21	22
#cabs	496	497	495	497	490	480	487	493	500	504

C. Simulation parameters

Table II summarizes the simulation parameters we use on our evaluation. The area size for HOP is defined by the Helsinki City Map used in the ONE [27], and we use the same dimensions for RWP. The SFO map size is inferred from the taxi traces. We use a radio range of 50 m for smart mobile devices for all scenarios, but also explore the larger-scale SFO scenario with 250 m because the mobile devices would be car-based. We choose 250 MB message buffer across all scenarios as, empirically, those don't cause message drops due to buffer overflow for up to 500 nodes at 1 message/node/hour. We define three different loads: 1, 2, and 4 messages per node per hour and three settings for message parameters: *variable* varies message size, TTL, and anchor zone for each message within a given range, whereas *fixed-500* and *fixed-2000* use constant parameters. Messages are generated across the entire simulation area for RWP and HOP, but their generation is limited to a central ("core") part as indicated by the solid line square in figure 4; the latter is to avoid areas with in little cab traffic influencing the results.

For the position errors, we run scenarios without GPS errors ("none") and with errors as per section IV-C with the parameters in table II ("60/10/0.1"). We vary the fraction of nodes having their own GPS between 10% and 100% and the intervals of reading the GPS position between constantly and once per minute in intervals of 15 s. We conduct 10 runs for each simulations with different random seeds and, for SFO, using different days from the traces for variable node mobility.

VI. EVALUATION

We first present the results of our synthetic mobility scenarios to explore the parameter space and then validate these findings using the traces. We ran 9,600 simulation settings for the synthetic models and 1800 for the trace-based model,

General parameters	
Area size	4500m (RWP, HOP), 60 × 90km (SFO)
Radio range	50 m (RWP, HOP), 50 m, 250 m (SFO)
Node buffer	250 MB
Position errors	
Fraction	$\rho \in \{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0\}$
Interval	$\delta \in \{0, 15, 30, 45, 60\}$ s
GPS error	none, ($\Delta U_1 = 60$ s, $\Delta U_2 = 10$ s, $f = 0.1$)
Messages	
variable	$r \in [200; 500]$ m, $a \in [500; 2000]$ m $T \in [1800; 10800]$ s, $s \in [100; 1000]$ KB
fixed-500	$r = a = 500$ m, $T = 3600$ s, $s = 500$ KB
fixed-2000	$r = a = 2000$ m, $T = 3600$ s, $s = 500$ KB
Traffic load	
low	1 message/node/hour
medium	2 messages/node/hour
high	4 messages/node/hour

TABLE II
SIMULATION PARAMETERS

with 10 seeds each, so that we have to constrain the following presentation to selected—representative—results.

A. Synthetic scenarios

Figure 5 depicts the simulation results for RWP with 100 and 1000 nodes; we begin with RWP because here some of the observed effects are particularly pronounced. Each point indicates the fraction of messages reached 95% of its intended lifetime, the error bars show the range from 75% (upper) to 100% (lower). Two expectations are obviously confirmed: increasing the message load reduces the success probability and denser networks yield better performance. We consistently see that having accurate GPS information improves performance compared to applying our error model. But we also find that delaying reading the GPS by different intervals does not appear to have a strong influence as the curves are fairly similar, shown as performance metric for different delays relative to $\delta = 0$ in figure 7a; we also note that in this regard it barely matter if GPS errors are present or not.

The most interesting findings are (1) the effect when varying the fraction of nodes supporting GPS; (2) the strong impact of restricting nodes learning their position to direct contacts with GPS-enabled devices vs. allowing nodes to obtain indirect positions as well; and (3) a difference between fixed and variable messages.

As for (1), for lower node densities, the performance appears better if fewer nodes have GPS enabled. This is because, especially in RWP, nodes meet rarely due to their unconstrained motion. So once a node without GPS carries a message, it depends on meeting another node before it can make a deletion decision if the node has moved out of the area. The net result is that the message survives *somewhere* in the system. Investigating the number of copies for each message clearly confirms this, with an average of less than two copies created per message. So, while messages may survive, they aren't useful because they aren't in their anchor zone. Having more nodes with GPS leads to even less replication because now messages are more frequently deleted upon the rare encounters as nodes determine that they

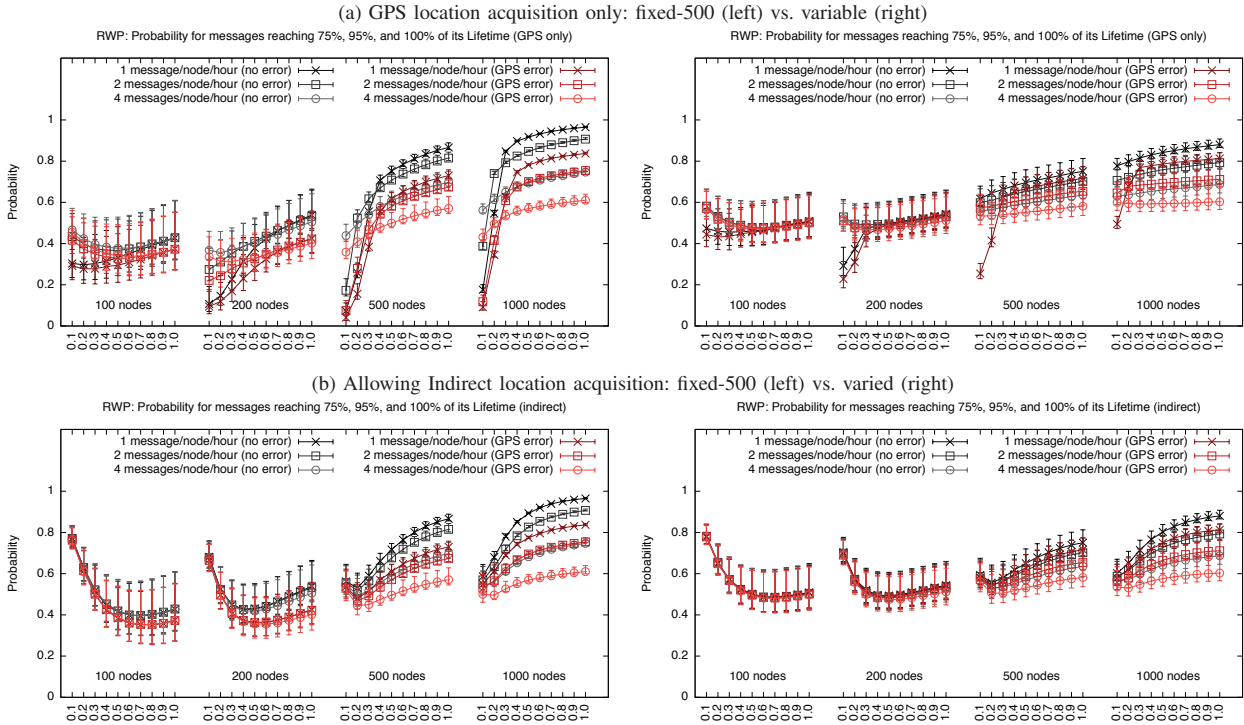


Fig. 5. RWP: Contrast of GPS errors vs. no errors for different node densities

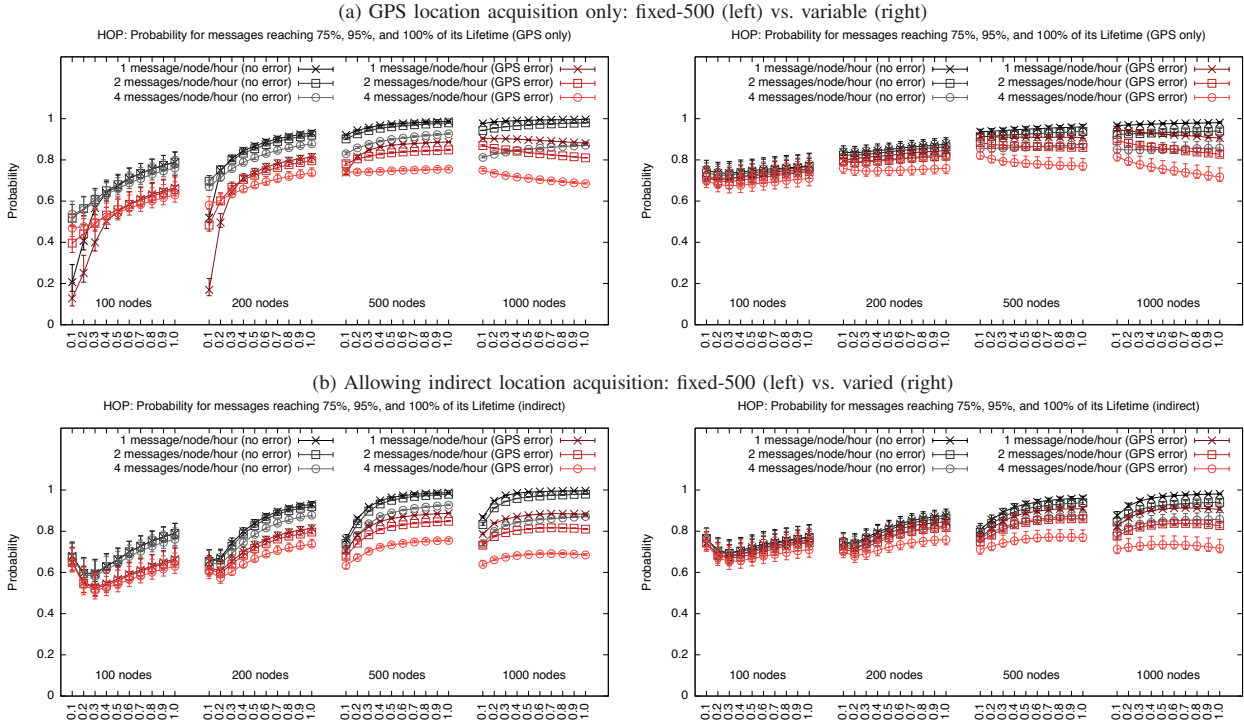


Fig. 6. HOP: Contrast of GPS errors vs. no errors for different node densities

moved left a message's anchor zone. Moreover, nodes only generate messages when they have a GPS reading (no matter how old), so they may create a message based upon a reading

just to delete it upon the next encounter as it was outside even created outside its anchor zone. With increasing node density, this anomaly disappears as nodes have the chance of updating

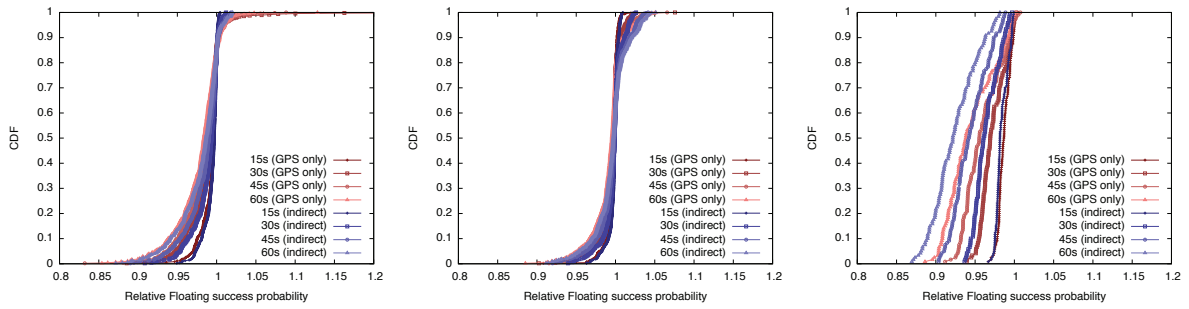


Fig. 7. Impact of different GPS reading intervals on Floating Content performance across all densities, loads and message types: a) RWP (left), b) HOP (middle), c) SFO (right)

their position more frequently so that we see the expected behavior for 1000 nodes (which gradually emerges already for 200 nodes and is clear for 500). For 500 and 1000 nodes, the marginal performance increase reduces as we surpass 50% of nodes supporting GPS.

Concerning (2), we find that enabling nodes to learn position from arbitrary peers in a transitive fashion rather than just from authoritative sources, i.e., GPS-enabled devices, makes the above anomaly effect more pronounced as incorrect positions propagate quicker, more nodes are ready to generate messages, and the accuracy of information goes down. Nodes may also delete message more readily if they encounter other nodes with outdated position information so that not meeting any nodes becomes a plus. As noted above, this means that useless (because mispositioned) messages may stay around.

Finally, (3) we observe a more pronounced performance difference across different parameters when using fixed messages compared to variable ones, especially in the denser scenarios. This is because our variable messages may have larger anchor zones and are, on average, thus less susceptible to being deleted due to position errors, which is confirmed as we see more mean copies of individual messages (some 20–30% for 1000 nodes, not shown). In addition, having different message attributes also allows more flexibility when prioritizing messages for replication (than just distance from the anchor point).

The findings for HOP mobility are qualitatively similar, but the overall performance is much better due to constrained node movement and thus more frequent encounters (see figure 6). The more frequent encounters also cause the anomaly observed for RWP to almost disappear and lead to the performance stabilizing at a smaller fraction of nodes with GPS support. It is most interesting to observe that the performance degrades with an increasing number of nodes supporting GPS with GPS errors (which does not happen in the absence of GPS errors). We attribute this to the “jumpiness” of our GPS error model. GPS-enabled nodes will exhibit less stable position properties and may occasionally jump out of the anchor zone, which then may cause content deletion. In contrast, nodes without GPS errors exhibit a more stable behavior as they only jump upon encounters. Introducing GPS reading intervals δ shows slightly less spread than with RWP and may even

have a slightly more positive impact because nodes are more constrained and meet more frequently so that the delayed reading may support further replication instead of deletion.

B. San Francisco cab traces

We also look at the GPS impact in a real world setting, the result summary for which is shown in figure ???. The overall performance is lower than RWP and HOP, which isn’t a surprise given that the area is much larger. To compensate this partly, we also run simulations with messages that have a fix anchor radius of 2 km (fixed-2000).

We see the same basic patterns as the number of GPS-enabled nodes increases (we would expect every cab to run GPS anyway) and that the impact of GPS errors is smaller (vehicles would probably have more accurate positions). If only GPS-enabled devices share positions, we need half of the node population to have GPS for the performance to roughly stabilize, otherwise the impact of the fraction of GPS-enabled nodes is less pronounced. The same reasoning as above applies, with cars moving faster making up for the lower density. The impact of the increased node velocity also becomes visible when looking at GPS reading intervals (see figure 7). There is virtually no positive error and the different reading intervals clearly separate.

For SFO mobility, we also explored a larger radio range (250 m) and find for low message loads of fixed-500 messages a Floating success probability of 0.44–0.17 and for fixed-200 messages of 0.79–0.87 and when allowing transitive (indirect) position sharing. When only using GPS-enabled nodes to acquire a position, the success rates are 0.23–0.71 for fixed-500 and 0.62–0.85 for fixed-2000 messages, thus improving performance expectedly. Moreover, the larger radio range (and thus more frequent encounters) appears to make the anomaly observed above disappear: we get monotonically increasing performance as more nodes have GPS.

VII. CONCLUSION

In our exploration of how three different types of position errors impact a location-based content sharing service show that such a service can be fairly robust against location errors provided that a sufficiently large fraction of nodes are GPS-enabled. GPS error ranges do play a role, but the impact

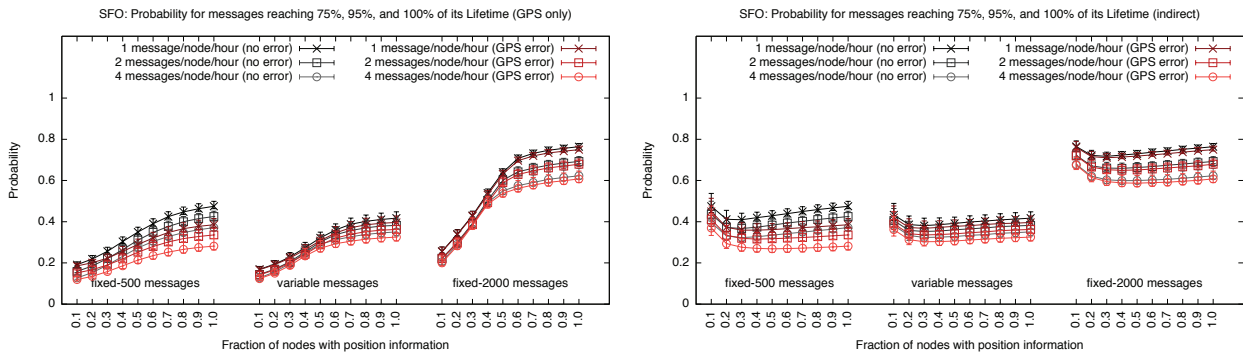


Fig. 8. SFO: Contrast of GPS errors vs. no errors for different message types and position acquisitions: GPS-only (left), indirect (right)

of other factors—such as the aforementioned fraction and the strategy for sharing location information—is more pronounced. We also find that synthetic models that approximate reality poorly (as RWP) may provide disproportionate results that are nevertheless useful for explaining issues. But content sharing services seem to suffer less from GPS errors when using models closer to or traces from reality.

After the extensive simulation studies presented here (which still only scratches the surface), our future directions are twofold: 1) devising an analytical model to properly characterize the underlying interdependencies of different parameters and 2) exploring GPS errors further, for more locations and more in detail for individual device behavior through measurement studies.

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